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Demographic Variations in Behavioral Biases and Their Influence on Financial Investment Decisions

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Abstract

Behavioural biases may influence financial decision-making, yet their demographic variation and relationships with investment outcomes remain insufficiently established among higher-education professionals. The present work investigates 6 behavioural biases and their relationship with retirement planning, risk preference and equity-oriented choice within portfolio of 420 higher education employees in the National Capital Region of India. Reliability assessment, comparisons across demographic groups, multiplicity correction, correlation analyses, heteroscedasticity-robust regression, and logistic regression were used to analyse responses from the questionnaires which were collected between January and April 2026. After multiple-testing correction, no demographic differences in behavioural-bias scores survived. There were virtually no correlations between the measured biases and financial literacy and planning for retirement (-0.08 to 0.09). Adding behavioural biases and financial literacy skills to the regression model accounted for just 0.4% of the variation in retirement planning. No focal predictor significantly explained equity orientation or risk tolerance. In the adjusted model, women scored lower than men on the retirement planning scale; but this result should be replicated independently. Most importantly, the chronically low internal consistency of the composite measures limits conclusions about the underlying psychological constructs. The results point the way to the requirement for appropriate measurement tools before a tool for keeping track of demographics and/or targeted financial interventions can be created.

Keywords: Behavioral Biases; Demographic Variation; Investment Decisions; Retirement Planning; Financial Literacy; National Capital Region

1. Introduction

Financial investment decisions are shaped not only by expected returns and risk assessments but also by cognitive limitations, emotional responses, and social influences. The role these play in shaping financial judgment and their consequences for financial outcomes, such as saving plans and how portfolios are allocated and the direction of long-term financial livelihoods, are explained by behavioural finance. Studies in recent years keep examining the effects of heuristic-driven biases on investment behaviour, as well as the conditions under which these impacts change from person to person (Sadeeq, 2026; Teixeira et al., 2026). Overconfidence, loss aversion, herding, focusing on specific instances or numbers (anchoring), mental accounting, and present bias are 6 behavioural biases that are especially relevant to investment decisions. Loss aversion is the psychological effect of losing something that is more intense than the equivalent gains and over-confidence is the third, which leads to over-estimation of personal knowledge and/or prediction accuracy. Herding is the following of other people's investment decisions; anchoring refers to over-reliance on the initial reference value and mental accounting is a phenomenon associated with the allocation of resources to separate subjective budgets. Present bias is the phenomenon that people tend to value present outcomes more than the future ones. These mechanisms have been explored in past studies with the contexts of risk-taking, decision quality, and financial advice (Islam et al., 2024; Nidhan et al., 2026; Hanif et al., 2026; Mitsudome & Huang, 2026).

These biases can be expressed differently among demographic groups, depending on whether some groups have more money and more resources to draw on, and are faced with different decision-making environments. Demographic trends should be treated with caution as a direct cause of behavioural patterns, however, and should

be empirically tested. Prior literature has examined how various population and institutional characteristics affect overconfidence, financial management and risk perception, but the results have to be interpreted in context of the population and institutional characteristics (Vaswani & Sirohi, 2026; Goyal & Kumar, 2026; Verma et al., 2025). Employees of higher educational institutions in the NCR of India constitute an appropriate population for the study of these relationships. Although both groups have the same level of education and face somewhat similar job prospects, the types of investments they make could vary based on their financial literacy, life situations and the employment and organizational setting. Previous studies with university teachers and government officials have examined the concepts of financial literacy, self-control, regret, and investment decision making (Nidhan et al., 2026; Prakash et al., 2026).

Moreover, the new systems based on AI are being developed, and there have been inquiries as to how behaviors relate to financial advice (Fedyk et al., 2026; Ioannou et al., 2026; Altıntaş & Yürekli, 2026; Şeker et al., 2025). For this reason, the aim of this study is to evaluate whether these biases differ across demographic groups, whether they are linked to retirement planning, attitude towards risk and equity-based composition of investments, and whether they are moderated by financial literacy, compared to retirement planning. Hence, the purpose of this study will be to determine if these biases vary across demographic groups, if they are associated with retirement planning, attitude towards risk and investment portfolio being cantered on equities, and if they are moderated when compared with attitude towards retirement planning and financial literacy. It combines Demographic comparisons, behavioural outcomes related to investments, and moderation analysis to perform a structured assessment of these behavioural constructs within higher-education, highlighting statistical reliability, effect sizes, confidence intervals, and proper control of multiple comparisons.

2. Literature Review

Behavioural finance theorises that the cognitive factors, emotional reactions and social processes influence investment decisions and can lead to systematic deviations from rational mind. The investor lens view is not about the investors all making consistent decisions objectively; this perspective looks at how the investors' psychological tendencies affect risk assessment, asset selection and financial planning. The study of heuristic-driven biases has been explored by Sadeeq (2026) and the links between risk preferences, behavioural biases and individual investment decisions explored by Teixeira et al. (2026). The above studies would serve as a basis for the analysis of various biases in a shared empirical context. In this work, the authors take into account overconfidence, loss aversion, herding, anchoring, mental accounting and present bias. The consequences they might have varies depending on the psychological mechanism involved. Self-confidence of individuals might lead to biased estimations of their knowledge, while loss aversion may play a role in making decisions to accept losses.

Herding involves psychological dependence of the investor on past investors' decisions; the subjective classification of financial resources is mental accounting and immediate satisfaction preference is present bias. In previous studies, these mechanisms have been identified as being related to risk propensity, regret, financial advice, and decision quality (Hanif et al., 2026; Islam et al., 2024; Mitsudome & Huang, 2026; Nidhan et al., 2026). Behaviour is also observed in the context of general mood and environment. Upadhyay et al. (2026) have looked at fear as a driving factor in decision-making, while Shreya et al. (2026) explored visceral states and social transmission bias. Investment in cryptocurrency and real estate are other examples that highlight the significance of studying biases on different assets classes (Manohar, 2025; Shahriari et al., 2025; Singh et al., 2023). Therefore, each of the six biases should be tested individually, and should not be expected to have the same effect on financial results.

Demographic characteristics are observed categories for examining differences in financial behaviour, but the measures do not stand in their own right as a basis for the explanation of the differences. Age, gender, income, education and occupation can relate to differences in income, financial resources, and financial exposure. Vaswani and Sirohi (2026) explored how younger generations in India are influenced by demographic factors in terms of overconfidence in financial knowledge, while Rosdiana et al. (2026) compared millennial and Generation Z investment orientation. In the study Goyal and Kumar (2026) explored the demographic and cultural factors along with psychological and social factors affecting personal financial management.

Gender and occupational context are two further aspects to add to the comparison. Hanif et al. (2026) added gender in the study of financial behaviour and Verma et al. (2025) integrated gender and locus of control in the study of risk perception and sustainable investing. Iram et al. (2026) examined key behavioural biases of women entrepreneurs with respect to their AI literacy and self-efficacy. The use of these studies can help demonstrate the importance of considering demographic differences but acknowledge that relationships found in one population may not necessarily carry over. Higher-education workers are included as a population because the employment conditions and institutional setting of employment can vary among organisations. The government employees were also included in the research that looked at financial decision quality and self-control, regret, investment decision-making, etc. (Nidhan et al., 2026; Prakash et al., 2026). But to measure and assess the demographic differences in the distribution of behavioural bias, one needs to make a direct measurement rather than assume based on level of education or employment stability. In the current study biases are therefore compared among nine levels of demographics, and the magnitude and statistical significance of differences between groups evaluated.

Financial literacy highlights an important deterministic variable in financial information reading and as well as investors' behaviour. Sadeeq (2026) and Hanif et al. (2026) took the view of literacy acting as a moderator for behavioural relations while Mohamad and Jamaludin (2026) explored behavioural relations ship with literacy specifically with saving behaviour. Singh et al. (2026) explored financial literacy and investment motives, while Prakash et al. (2026) discussed its impact on government employees' investment choices. Financial literacy and self-confidence are distinct concepts when analysing overconfidence. Because both financial knowledge and confidence in finance and investments are related to the investment risk tolerance, it is important to study each of these constructs separately, Otaify and Ebeid (2026) continued. Financial literacy, investment behaviour and retirement age were linked by Tavor and Teitler-Regev (2026), which formed a foundation for contemplating literacy in long-term financial planning. Financial literacy can then be studied as a predictor of measures of investment performance and as a potential moderator of the link between behavioral biases and retirement planning. But moderation can only be defined empirically based on the interaction analysis, and not from a simple financial knowledge presence alone. This study therefore investigates whether the relationship between behavioural biases and retirement planning is different for persons who are more versus less financially literate.

Investment behaviours are influenced by plan for retirement, tolerance for risk, and portfolio structure with respect to holdings of equity shares. Retirement planning refers to preparing for future needs, tolerance for risk is a willingness to deal with risk, and the composition of the portfolio pertains to putting money in stocks and other equity-oriented assets. These results may overlap but should not be used as synonyms for each other. Both Tavor and Teitler-Regev (2026) and Islam et al. (2024) were studies which related financial literacy to retirement-related decisions and financial risk propensity to behavioural biases, respectively. The quality of the measurement is also crucial for the reliability of the interpretation. Both de Waal et al. (2024, 2026) and Sholevar (2026) discussed the need to consider the structure of questionnaires when creating interpretive composite scores for financial distress and the difficulties arising from the introduction of biased judgments in AI-driven financial customer analysis. These studies strengthen the notion that there is a need to separate construct measure from ensuing statistical analysis.

There is very little research considering the potential differences in six behavioural biases among the employees of higher educational institutions in the NCR region of India and their linkages with several investment outcomes. Consequently, this study examines differences on the behavioural biases measured by the score across various demographic groups (H1), the relationship between the behavioural biases as measured by the score after controlling for the demographic variables and the financial literacy variables (H2), the moderating effect of financial literacy in this relationship (H3) and the link between behavioural biases as measured by the score and the risk tolerance as well as equity-oriented portfolio composition (H4). The framework being proposed combines a system of comparison of the demography, a system of analysis of the outcomes and a testing system using moderation. The findings are statistically rigorous in that they are supported by reliability estimates, effect sizes, confidence intervals and appropriate multiple comparison corrections.

3. Research Methodology

The study used a quantitative, cross-sectional survey research design to understand the demographic differences in behavioural biases and the components of relationship between the demographic differences and financial investment alternatives. Primary data were gathered from the respondents (420) working in Higher Educational Institutions (HEIs) during the National Capital Region in India from 15 January 2026 to 15 April 2026. The data is based on responses to a structured questionnaire, and is not simulated observations, but actual data from the population of the study. The analytical tool that has been developed combines group results comparisons with regression modelling and moderation analysis, and explores the relationships between behavioural biases and financial literacy with respect to investment outcomes. “Similar approaches based on surveys have been used to look into behavioral and contextual factors influencing personal choices (Chen et al., 2026; Omotoso & Omotayo, 2024).

The respondents were teachers, research and administrative staffs in total of 420. The following demographic information was collected: Gender, Age group, Marital status, highest Education qualification, Designation, Type of Institution, Years of service, monthly family income, Career stage. These variables were employed to investigate differences in the scores for the behavioural bias items for the different groups of respondents. Six behavioural biases were measured with 24 five-point agreement items, 4 items for each construct, the questionnaire is the overconfidence, the loss-aversion, herding, anchoring, mental accounting, and present bias. The results were presented as composite scores, which were derived by means of the items, and ranged with higher scores representing higher degrees of agreement with the statements.

The following seven five-point items were used to assess retirement planning: preparation for retirement, savings behavior, future financial needs, and planning related activities. Risk tolerance was classified as low, moderate, or high, while portfolio composition was categorized as equity-oriented, debt-oriented, hybrid or balanced, and real assets. Financial literacy was self-reported as five multiple choice questions of compound interest, inflation, risk diversification, bond prices and comparing loan interest. One point was awarded for each correct response, giving the possibility of 0 to 5 points. The measurement structure allowed for an analysis of the differences across the demographics, the relationship between the behavioral biases and the investment outcomes, and the moderating effects of the financial literacy in the same lens on which the analysis was conducted.

4. Results and Discussion

Table 1. Demographic characteristics of the respondents (N = 420)

Variable	Category	n	%
Gender	Male	189	45
	Female	210	50
	Prefer not to say	21	5
Age group (years)	Below 30	42	10
	31–40	126	30
	41–50	118	28.1
	51–60	92	21.9
	Above 60	42	10
Marital status	Single	147	35
	Married	231	55
	Other	42	10

Highest qualification	Postgraduate	126	30
	PhD	189	45
	Post-doctoral	105	25
Designation	Assistant Professor	126	30
	Associate Professor	92	21.9
	Professor	76	18.1
	Research Staff	76	18.1
	Administrative Staff	50	11.9
Institution type	Central University	147	35
	State University	105	25
	Private University	105	25
	Deemed University	63	15
Years of service	Less than 5	92	21.9
	5–10	118	28.1
	11–20	126	30
	More than 20	84	20
Monthly household income (₹)	Below 50000	63	15
	50001–100000	147	35
	100001–150000	126	30
	Above 150000	84	20
Career stage	Early Career	126	30
	Mid-Career	160	38.1
	Late Career	134	31.9

The study analyzed 420 collected responses from employees of higher-education institutions in India's National Capital Region (As presented in Table 1). There were 50.0% women, 45.0% men, and 5.0% persons who did not state their gender. Respondents aged 31-40 years constituted 30.0% of the sample, followed by those aged 41-50 years (28.1%). The most frequently encountered educational category was doctorate (45.0%) followed by assistant professors (30.0%). The largest share of institutions was from central universities (35.0%). The biggest income earner was people earning between ₹50,001 and ₹100,000 per month (35.0%) with mid-career earners at 38.1%. The distribution has representation across nine demographic characteristics, allowing comparisons of behavioral-bias scores across the characteristics recorded. The representation was not consistent, however, as the sample with an undisclosed gender numbered 21 and some occupancy categories and institutional categories were smaller than the main ones. Then, the differences between categories for smaller sample sizes should be interpreted with respect to sampling precision. These features reflect the population with which the next set of statistics are compared.

4.1 Measurement Quality and Score Distributions

The six behavioral-bias scores fell into a fairly restricted range, as shown in table 2, Descriptive statistics. Loss aversion recorded the highest mean (M = 3.54, SD = 0.54), followed by mental accounting (M = 3.41, SD = 0.53), anchoring (M = 3.39, SD = 0.53), overconfidence (M = 3.29, SD = 0.54), and herding and present bias (both M = 3.21). The results for all six exceeded the middle point of 3.00 on this scale. They all had a similar range in average responses with standard deviations from 0.53 to 0.55. The mean score for the literacy competency was 3.85 and the standard deviation was 0.90 out of 5. An average person's retirement plan was 3.29 with a standard deviation of 0.38.

Table 2. Descriptive statistics, distributional characteristics, and internal consistency of composite scores

Score	Items	M	SD	Skewness	Kurtosis	Cronbach's α
Overconfidence	4	3.29	0.54	-0.22	-0.10	0.031
Loss aversion	4	3.54	0.54	-0.27	0.04	0.113
Herding	4	3.21	0.53	-0.12	-0.19	-0.059
Anchoring	4	3.39	0.53	0.01	-0.19	0.023
Mental accounting	4	3.41	0.53	-0.24	-0.05	0.044
Present bias	4	3.21	0.55	-0.11	-0.04	0.073
Retirement planning	7	3.29	0.38	0.00	-0.09	-0.161
Literacy	5	3.85	0.90	-0.56	0.17	-0.116

The skewness and kurtosis estimate values ranged from moderate for the 6 bias scores, indicating that heights were not significantly skewed. Therefore, lack of distributional shape does not necessarily indicate lack of measurement validity, or even mean that all model assumptions are not being met. More important, the Cronbach's alpha coefficients were nearly zero for all of the constructs: overconfidence (0.031), loss aversion (0.113), herding (-0.059), anchoring (0.023), mental accounting (0.044), and present bias (0.073). Retirement planning and literacy also produced negative reported coefficients of -0.161 and -0.116, respectively. These are well short of the benchmark reliability of .70 accepted in the convention. This measurement pattern is of a detectable dimension that impinges upon the meaning. Items with low or negative alpha scores are not good indicators of coherence of composite scales as they are scored. There are several possible causes, such as different item phrasing, differences in item direction, or low inter-item covariance, but none of the available results can determine the correct cause.

Therefore, item coding and reverse-scoring requirements need to be checked prior to the finalization of the coefficients. Similarly, Sholevar (2026) stated that the dimensionality of the questionnaire should be considered instead of treating items grouped together as one construct. The mean-score profile is presented in Figure 1. The

highest and lowest values of the numerical interval of the bias means was 0.33 on the 5-point scale. The descriptive results thus reveal that there is an item group-wise disparity in the mean level of agreement, but the relatively small margin does not provide grounds for concluding that one mechanism dominates investment behaviour. The use of loss aversion in these interpretations is based on the highest mean, however, because of the scale limitations, this should be interpreted descriptively.

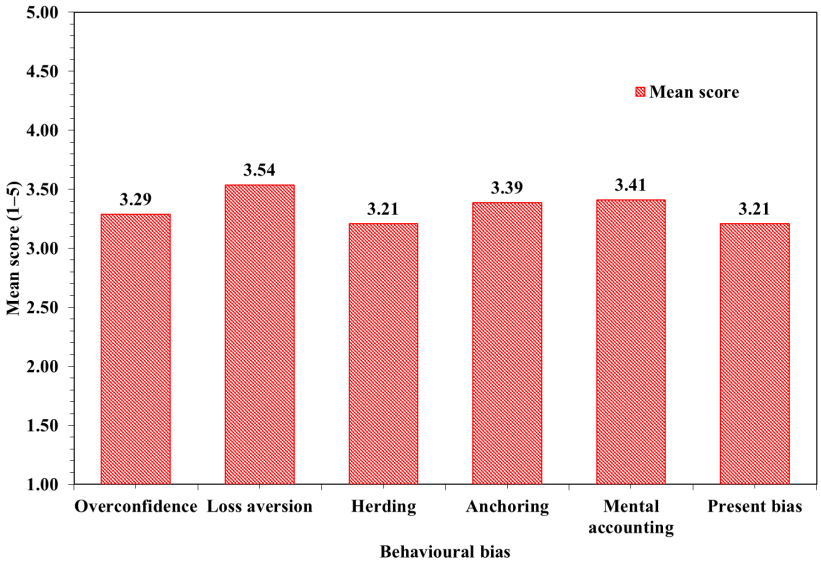


Figure 1. Mean scores for the six behavioural-bias item groups on a five-point scale

The reliability coefficients are compared with the conventional threshold in Figure 2. The significant separation from reported coefficients and threshold values further emphasizes the need to separate item average scores from valid latent constructs. In this context, the subsequent "interpretation" of the demographic analyses is thought of as a comparison of observed composite means in place of a narrowing of differences in underlying psychological dispositions.

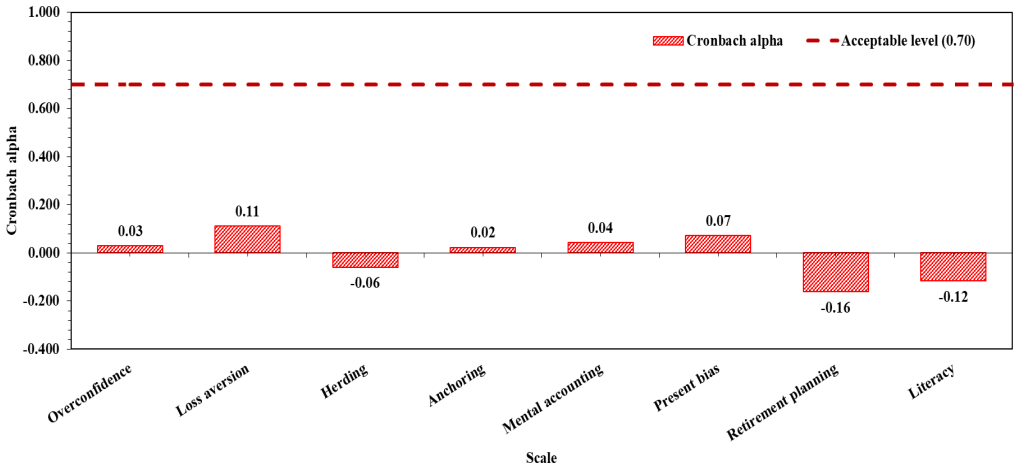


Figure 2. Reported Cronbach's alpha coefficients compared with the 0.70 reference threshold

4.2 Demographic Variation in Behavioural Biases

The first research question examined whether behavioral-bias scores varied across nine demographic characteristics (Table 3). The analysis included 54 demographic-by-bias comparison and retirement planning and literacy was assessed separately in a family of 18. There were 3 out of 54 bias tests that came to nominal

significance at the 5% level. However, none remained significant after Holm correction. However, under the given multiple-comparison procedure, the evidence is not consistent with H1.

Table 3. Summary of demographic comparisons for behavioural biases, retirement planning, and financial literacy

Demographic variable	Groups	Smallest p (6 bias tests)	Smallest Holm p	Largest η^2	p (retirement)	p (literacy)
Gender	3	0.068	1.000	0.013	0.004	0.133
Age	5	0.163	1.000	0.016	0.441	0.080
Marital	3	0.077	1.000	0.012	0.692	0.761
Education	3	0.108	1.000	0.011	0.133	0.182
Designation	5	0.043	1.000	0.023	0.755	0.418
Institution	4	0.092	1.000	0.015	0.322	0.573
Years of service	4	0.123	1.000	0.014	0.132	0.786
Income	4	0.010	0.549	0.027	0.526	0.254
Career stage	3	0.194	1.000	0.008	0.959	0.204

The poverty variable generated the lowest unadjusted p-value of any of the bias comparisons ($p = .010$), although the largest eta-squared value of its six outcomes was .027. Of the remaining demographic factors, the one yielding the next smallest reported p-value was designation ($p = 0.043$) and all other demographic factors had no bias (reported p-values > 0.05), except for income related contrasts. After Holm adjustment the smallest p-value for income was 0.549. Thus, the results are not statistically significant enough to indicate a difference in average bias score between the observed demographic categories.

Table 4. Group means and test statistics for comparisons reaching nominal significance before adjustment

Comparison	Group means	F test	p	η^2	Holm p	Kruskal–Wallis p
Gender × Retirement planning	Male 3.36; Female 3.24; Not disclosed 3.24	F(2, 417) = 5.56	0.004	0.026	0.075	0.007
Income × Mental accounting	<50k 3.58; 50–100k 3.33; 100–150k 3.39; >150k 3.46	F(3, 416) = 3.82	0.010	0.027	0.549	0.015
Income × Overconfidence	<50k 3.38; 50–100k 3.23; 100–150k 3.38; >150k 3.18	F(3, 416) = 3.42	0.017	0.024	0.916	0.038
Designation × Mental accounting	Asst. Prof. 3.30; Assoc. Prof. 3.51; Professor 3.41; Research 3.42; Admin. 3.48	F(4, 415) = 2.48	0.043	0.023	1.000	0.033

Four comparisons (Table 4) were identified as nominally significant across the broader analysis. These included the gender and retirement planning category, the income and mental accounting category, the income and overconfidence category and the designation and mental accounting category. The unadjusted p-values for their findings ranged from 0.004 to 0.043, and the effect sizes were small, with eta-squared values ranging from 0.023 to 0.027 (bias comparisons), and 0.026 (retirement planning). The Holm-adjusted values were 0.075 for Gender and Retirement Planning, 0.549 for Income and Mental Accounting, 0.916 for Income and overconfidence and

1.000 for Designation and Mental Accounting. Therefore, none fulfilled the traditional 0.05 significance level post adjustment. The group means also provide little evidence of consistent demographic gradients. However, mental accounting was highest when income was lowest (M = 3.58), while the overconfidence means were the same for the lowest income bands and the third income band (both M = 3.38). Patterns shown do not necessarily suggest a regression toward the mean between household income and either score.

The difference between the scores of assistant and associate professors was small and not significant theoretically when adjusted for correction to designation, with mental accounting mean at 3.30 for assistant professors and 3.51 for associate professors. The Kruskal–Wallis tests for nominal significance correspond with the mean values of the ANOVA, and therefore were used as a consistent unadjusted comparison across the two tests. Gender parity should be introduced to planning for retirement with the same caution. The average for men was 3.36, while the average for females was 3.24 and the non-gendered population had an average of 3.24. The unadjusted p-value was 0.004 but the adjusted p-value of .075 did not meet the prespecified level of significance. This small difference in the means of the two groups should not, therefore, be seen as a definite indication of this gender effect.

The gender-specific bias profiles are shown in Figure 3. The mean scores of men and women were similar overall, but different relative scores on the six biases. There were 21 respondents who did not specify gender in which lower means for some were noted; just 21 individuals were in this group. The findings cannot answer whether there is a consistent difference between this smaller group and the other groups. The result offered a useful contrast with studies that suggested gender as a moderator of financial behaviour (Hanif et al., 2026; Verma et al., 2025), but, due to the variation in sample, and analytical model, the results cannot be directly compared to the data from the present study.

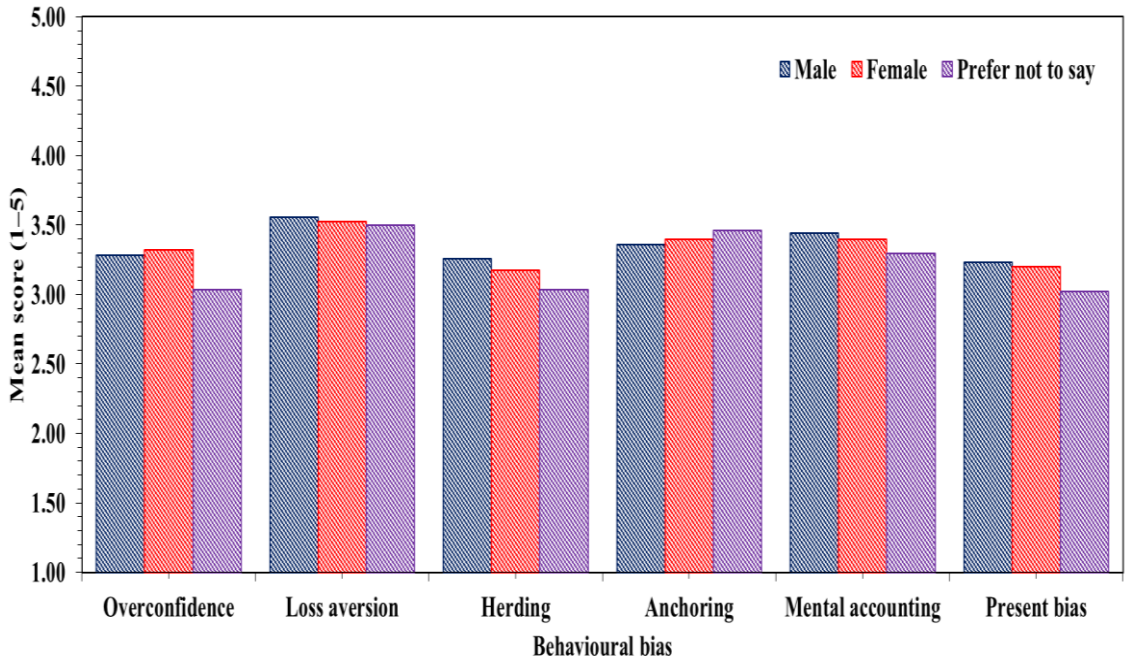


Figure 3. Mean behavioural-bias scores by self-reported gender category

Age-group comparisons likewise showed no consistent progression across the five categories. Although there was a descriptive difference between the groups with the youngest group showing the highest anchoring mean, there was no statistically meaningful difference across ages. The age-distribution is displayed in Figure 4. In contrast with generational studies carried out by younger populations of investors (Vaswani & Sirohi, 2026; Rosdiana et al., 2026), this study fails to make any distinction between generations. In the present sample, however, the respondents are those employed in HEIs and results, therefore, are not generalizable to all investors.

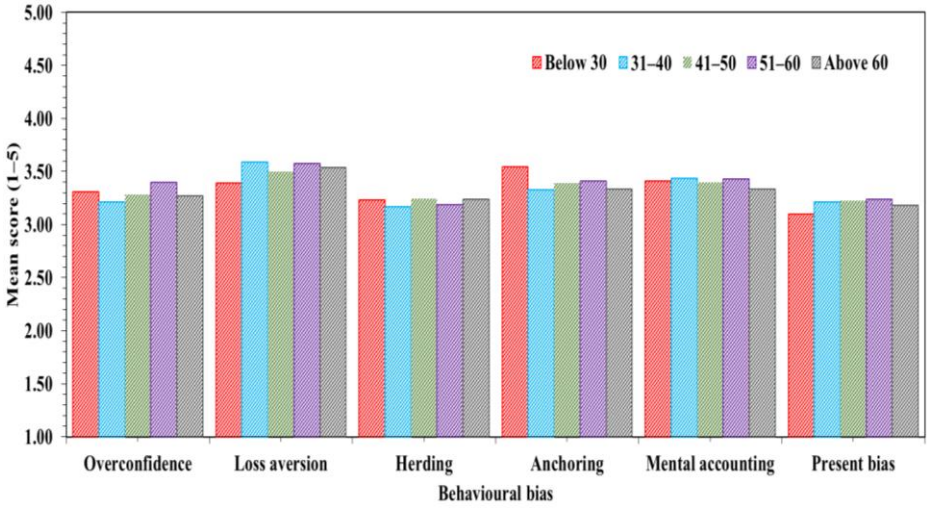


Figure 4. Mean behavioural-bias scores across the five age groups

Figure 5 also illustrates the magnitude of demographic differences through the effect size. The estimated means of eta-squared values were between about 0.005 and 0.017 with the largest average estimated by income, followed estimated by designation. From these values one can claim that only a small percentage of the variance in the observed bias scores could be explained by the demographic categories. The sensitivity analysis reported suggested that the effects of an eta-squared of 0.02 to 0.03 would be measurable with 80% power in the above conditions. Smaller differences are not precluded by the current results, but the results do not indicate substantial separation of the two. This interpretation follows the significance of acknowledging investor heterogeneity but not necessarily large differences across subgroups (Berliner et al., 2025).

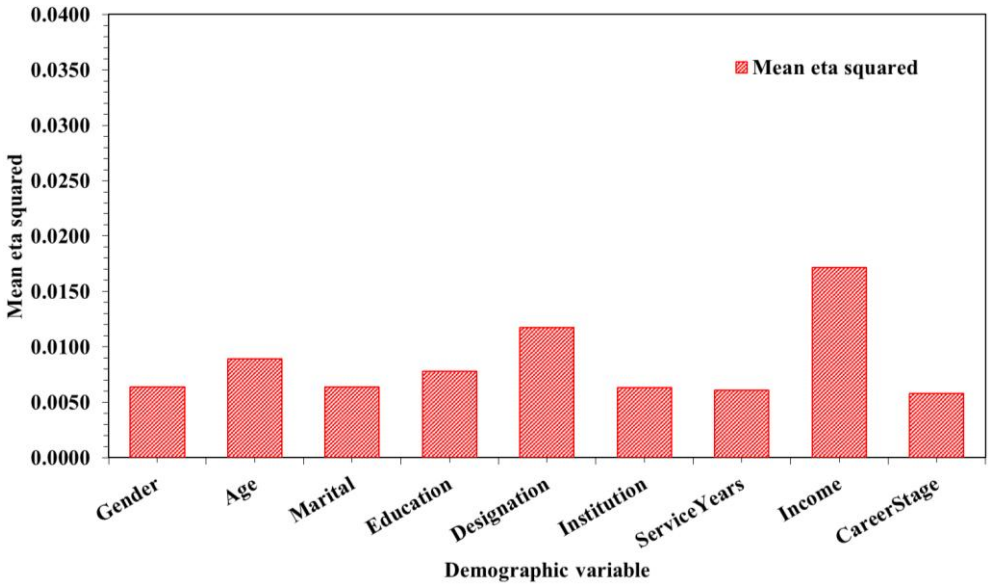


Figure 5. Mean eta-squared effect sizes across the six behavioural-bias comparisons for each demographic characteristic

4.3 Associations Among Behavioural Biases, Financial Literacy and Retirement Planning

Pearson correlation analysis was conducted to examine the relationships among six behavioral biases, financial literacy and retirement planning among 420 higher-education employees. The correlations are uniformly weak appearing in Table 5, being in the range of about -0.08 to 0.09. Overconfidence had the highest positive correlation (r = 0.09) while loss aversion had the highest negative correlation (-0.08) with mental accounting. None of the

correlations were significant at the 0.05 level (two-tailed) with the lowest two-sided p value being 0.053. These results provide no statistically significant evidence of linear associations among the measured variables in the present sample.

Table 5. Pearson correlations among behavioural biases, financial literacy and retirement planning

Score	1	2	3	4	5	6	7	8
1. Overconfidence	-							
2. Loss aversion	-0.01	-						
3. Herding	-0.03	-0.07	-					
4. Anchoring	0.02	-0.02	0.07	-				
5. Mental accounting	0.04	-0.08	0.00	-0.05	-			
6. Present bias	0.09	0.04	0.03	0.01	-0.01	-		
7. Literacy	0.03	-0.03	0.01	0.02	0.02	0.06	-	
8. Retirement planning	0.04	0.04	-00.00	-0.02	0.02	0.01	-0.01	-

Financial literacy showed negligible correlations with overconfidence ((r = 0.03)), loss aversion ((r = -0.03)), herding ((r = 0.01)), anchoring ((r = 0.02)), mental accounting ((r = 0.02)) and present bias ((r = 0.06)). There was also little correlation between its dimensions and retirement planning (r = -0.01). So, there did not appear to be a systematic pattern of lower reported bias scores or higher retirement planning for test takers with higher scores on the five-item knowledge test. This finding is contrary with the link between financial knowledge and "overconfidence" as discussed by Otaify and Ebeid (2026). However, the comparison is constrained since the aim of instrument measure is not to judge the difference between perceived and real knowledge but rather the real knowledge.

The initial reliability constraint is introduced by the reliability of the behavioral-bias composites. Where internal consistency is very low, measurement errors may reduce the correlation between the scores obtained and make relationships between the constructs seem inexistent. The fact that almost all the coefficients are zero should be not taken as evidence for the independence of the behavioral biases affecting the estimates. On the contrary, they point to the absence of any real empirical relationships with the current measures of composites. The results, therefore, highlight reliability of the measures before making any theoretical inferences about the relationships between behavioral biases, financial literacy, and plans for retirement.

4.6 Regression Results for Retirement Planning

Hierarchical regression analysis was used to evaluate the explanatory contribution of behavioral biases, financial literacy and demographic characteristics to retirement planning. In Model 1, no variance was explained by the model (R^2 = 0.4%) and adjusted (R^2) was -0.010 as reported in Table 6. The overall model was not statistically significant, (F(6,413) = 0.29, p = 0.944). All of the coefficients corresponding to overconfidence, loss aversion, herding, anchoring, mental accounting and present bias were small in comparison with their standard error. The outcome findings of this study suggest that none of the six measured bias scores explained much, when taken together, regarding to retirement planning.

Table 6. Regression of retirement planning on behavioural biases, financial literacy and demographic characteristics

Predictor	Model 1 B (SE)	Model 2 B (SE)	Model 3 B (SE)
Overconfidence	0.016 (0.018)	0.016 (0.018)	0.012 (0.019)
Loss aversion	0.015 (0.019)	0.015 (0.019)	0.011 (0.020)
Herding	0.001 (0.018)	0.001 (0.018)	-0.006 (0.019)
Anchoring	-0.008 (0.018)	-0.008 (0.018)	-0.006 (0.019)
Mental accounting	0.006 (0.019)	0.006 (0.019)	0.001 (0.021)
Present bias	0.003 (0.020)	0.003 (0.020)	0.000 (0.021)
Literacy	-	-0.005 (0.019)	-0.012 (0.020)
Gender: female (ref. male)	-	-	-0.131 (0.041)**
Qualification: postgraduate (ref. PhD)	-	-	-0.093 (0.045)*
Other demographic controls	No	No	Yes (23)
R^2	0.004	0.004	0.083
Adjusted R^2	-0.010	-0.013	0.007
F (df)	0.29 (6, 413)	0.26 (7, 412)	1.09 (32, 387)
p (model)	0.944	0.970	0.339

Introducing financial literacy in Model 2 did not improve explanatory performance. The coefficient of determination was 0.004, adjusted (R^2) was -0.013 and the overall model was not significant ($F(7,412) = 0.26$, $p = 0.970$). There was a negative correlation between financial literacy and having a robust Standard Error (0.005), with a standard error of 0.019. This estimate is almost null and does not support an independent association with participation in retirement planning, after controlling for the behaviour-bias scores. Based on the regression evidence, then, H2 was not supported. However, the weak reliability of the bias composites limits the extent to which these results can be generalized to the underlying psychological constructs.

Model 3 unadjusted (R^2) is 0.083 with an adjusted (R^2) of 0.007. The overall model remained nonsignificant, ($F(32, 387) = 1.09$, $p = 0.339$). Difference between the unadjusted (observed) and the adjusted (standardized) estimates will reflect the difference in the term “observed” and “standardized” but does not necessarily imply either more convincing or more convincing performance in terms of the numbers of predictors. The gender difference was using a negative coefficient when compared to male respondents ($B = -0.131$, $SE = 0.041$, $p<.01$). The postgraduate respondents also had a lower coefficient than a doctoral respondent ($B = -0.093$, $SE = 0.045$, $p<0.05$). However, these individual results were from a model with 32 predictors with unadjusted significance. For each coefficient, it should be interpreted without showing any definitive demographic difference, before the introduction of multiple comparison control and independent reproduction.

The standardized model’s coefficients and 95% CIs are depicted graphically in Figure 6 for Model 2. None of the estimated associations is different than zero at the conventional 5% significance level since all intervals cross this mark. The amount of the coefficient is also low, which means that signals contained in the measured composites are not very valuable. The confidence intervals however are not intended as an indication of the absence of any effects of practical importance (for which appropriated equivalence bounds would need to be pre-specified and subjected to an equivalence test). The results are opposite from the studies which are related to irrational financial behaviour and behavioral biases by investment decision quality (Nidhan et al., 2026; Jannatunnesa et al., 2026).

Partly this divergence could be due to differences in outcome definition and quality of outcome measures, since self-reported retirement planning is not directly a measure of quality of investment decision.

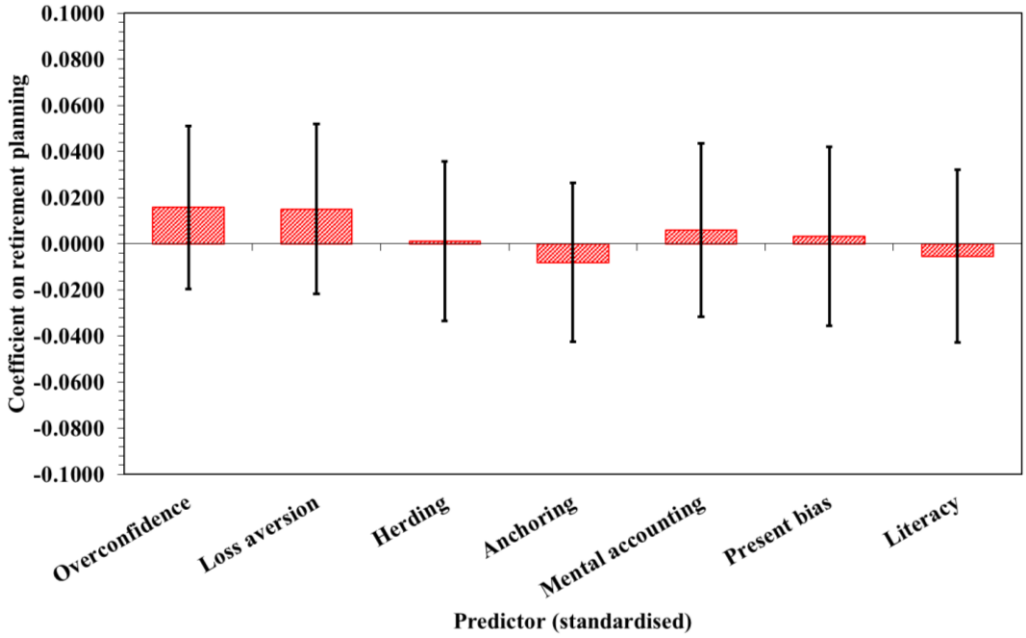


Figure 6. Standardised coefficients for retirement planning with 95% confidence intervals

The second moderation analysis did not yield significant interactions between FL and any of the 6 behavioral biases. The adjusted explanatory power also dropped to close to zero. Therefore, the hypothesis that H3 is correct was not supported. Based on the findings of this research, a potential mechanism for the role of financial literacy in intervening in the relationships between heuristic biases was not obtained, as was discussed in Sadeeq (2026) and Hanif et al. (2026). Measurement error may result in less evidence for the proposed relationships due to weak main effect estimates, and if main effects are not present there is less evidence for the proposed relationships.

4.7 Risk Tolerance and Equity Orientation

To determine the association between behavioral biases and investment preferences in terms of 'equity orientation' or 'risk tolerance', two logistic regression models were used: the binary logistic regression (for the equity orientation) and ordered logistic regression (for the risk tolerance). Table 7 shows the odds ratios (and confidence intervals and significance levels) for each of the seven main predictors. All 95% CI for the ORs included one and none of the coefficients was statistically significant in either model. These results provide no statistically significant evidence that the measured behavioral biases or financial literacy were associated with either outcome after accounting for the demographic controls. For equity orientation, the odds ratios ranged from 0.98 for mental accounting to 1.13 for present bias. The estimate for present bias was positive, but its confidence interval included one (OR = 1.13, 95% CI [0.91, 1.40], (p = 0.266)).

For risk tolerance, the overconfidence coefficient indicated lower estimated odds of greater risk tolerance (OR = 0.88, 95% CI [0.72, 1.06], (p = 0.168)), whereas present bias had an estimated odds ratio of 1.13 (95% CI [0.93, 1.36], (p = 0.219)). Both of these associations were not statistically significant and the intervals allow for uncertainty in the direction and strength of the underlying relationships. The pseudo-R^2 obtained in the equity-oriented model was 0.028 which means there was limited improvement over the intercept-only model according to this measure. The reported likelihood-ratio tests were nonsignificant for equity orientation ((X2(32) =15.3, p = 0.994)) and risk tolerance ((X2(32) = 37.9, p = 0.217)). So, none of the range of objectives was supported for H4. A nominal significant result for single respondents compared to married respondents was found for risk tolerance, with lower estimated chances of higher risk tolerance being observed for single respondents. The finding should

be interpreted with caution however, as it is a preliminary finding and multiple predictors were explored without a multiplicity correction.

Table 7. Odds ratios from logistic models of equity orientation and risk tolerance

Predictor	Equity-oriented OR [95% CI]	p	Risk tolerance OR [95% CI]	p
Overconfidence	1.02 [0.82, 1.27]	0.829	0.88 [0.72, 1.06]	0.168
Loss aversion	1.01 [0.82, 1.24]	0.951	1.04 [0.86, 1.26]	0.669
Herding	1.11 [0.88, 1.39]	0.373	1.00 [0.83, 1.21]	0.981
Anchoring	1.09 [0.87, 1.36]	0.471	1.02 [0.85, 1.22]	0.840
Mental accounting	0.98 [0.79, 1.21]	0.831	0.94 [0.78, 1.13]	0.507
Present bias	1.13 [0.91, 1.40]	0.266	1.13 [0.93, 1.36]	0.219
Literacy	0.99 [0.80, 1.24]	0.951	0.96 [0.80, 1.15]	0.650
LR χ^2 (df), p	15.3 (32)	0.994	37.9 (32)	0.217
McFadden pseudo R^2	0.028			

The results contradict the condition association among behavioural bias and financial confidence with risk propensity as discussed by Islam et al., (2024) and Otaify & Ebeid (2026) while buttressing the importance of consideration of measurement quality and context as discussed by Musah and Adenutsi (2025). The equity orientation refers to the composition of the portfolio, the choices of which could be affected by investment opportunities and product availability and institutionalisation. Risk tolerance, however, is defined as a desired attitude towards financial risk. The difference is significant because it suggests that an individual's investment preferences might not actually reflect his or her choices of holding a specific stock. These institutional influences were not measured directly and so their contribution should, therefore, be regarded as a plausible explanation, rather than a finding.

4.8 Financial Literacy Profile

The distribution of financial literacy scores (5-point scale from the number of correct answers to five questions) is shown in figure 7. About 183 people scored 4, about 103 people scored 5 and about 100 people scored 3. Approximately 30 respondents scored two, while only a very small number obtained zero or one correct answer. So, 75% of the participants or more answered 3 or more questions correctly and a significant number answered 4 or 5 questions. Observations clustered at the top reflect limited variation in financial knowledge measured by this observation scale, which can limit the capacity to identify linkages between financial knowledge measures and behaviour and financial outcomes. The distribution highlights the fact that relationships between financial literacy and other variables measured could not be seen to differ significantly. A limited score range may have led to the nonsignificant findings, although it does not by itself establish that findings were nonsignificant due to a ceiling effect.

In addition, the five items address relatively shallow content domains in the assessment of financial knowledge and do not measure how people apply such knowledge in decisions that involve multiple factors. The results therefore do not suggest that financial literacy is unimportant for retirement planning, but instead call for broadening the measurement of financial literacy. The concepts of conventional financial and digital financial literacy are differentiated in research which provides foundation and structure for developing a more comprehensive assessment done by Yadav et al., (2026), Zaimovic et al., (2025), and Hao et al., (2026). In future studies, more challenging questions and measures of perceived financial knowledge should be included. Comparing what people think they know to what they are actually doing would allow the evaluation of the

calibration effect, especially as it relates to overconfidence. Such a design would also help distinguish respondents who possess limited knowledge from those who overestimate their financial understanding.

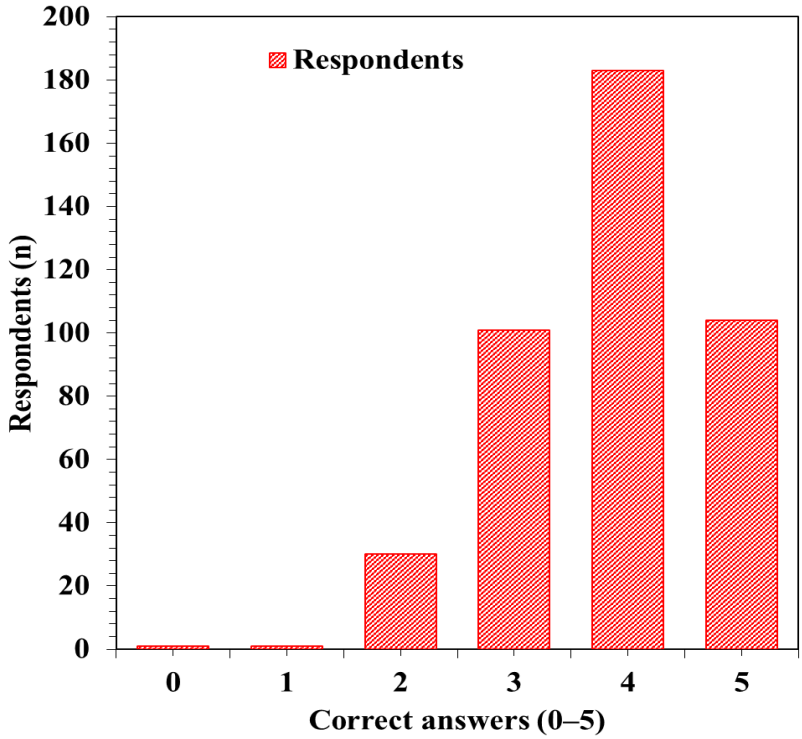


Figure 7. Distribution of financial literacy scores

4.9 Synthesis and Implications

Across the correlation, regression and logistic analyses, the measured behavioral-bias scores and financial literacy did not demonstrate statistically significant associations with retirement planning, equity orientation or risk tolerance. In fact, the reported analyses did not support H2, H3 and H4. The findings here reflect less evidence to support predictive power of the current composite measures in the population sampled. But because the scales in the behavioral-bias are not internally consistent, it is unclear whether the underlying psychological mechanisms are not present. The difference between “there is not statistically significant evidence” and “the evidence is that a negligible amount is important to using the results. The methodologically relevant suggestion is building measurement validity within the predetermined tasks of demographic profiling and the activity of financial interventions design.

The exploratory nature of the gender difference in retirement planning needs to be replicated with a pre-specified analytical approach and correction for multiple comparisons. In more general terms, the results indicate that demographic factors do not necessarily mark a person's likelihood of exhibiting behavioral biases nor financial requirements. Existing financial technology and financial literacy literature also points to the meaning of capability and conditions of access and engagement (Aftab et al., 2025; Hao et al., 2026) and the role of the wider financial-service climate for consumer protection (Ryan et al., 2026). Therefore, the technological systems supporting advisory services need to be assessed with regards to their responsiveness in meeting tangible financial needs, delivering transparency and explainability, and fostering user confidence (Fedyk et al., 2026; Ioannou et al., 2026). Combination of several economic and lifestyle factors together (interpretable approach) can also define a helpful direction for further assessment (de Waal et al., 2024).

Theoretically speaking, the results do not confirm, but neither contradict, the cognitive, affective and social mechanisms that are suggested in behavioral finance. Existing measurement restrictions make it difficult to compare these mechanisms, and the results indicate that aggregation of the responses to the questionnaires did not

work out as a helpful prediction of the selected financial outcomes. The latter interpretation is consistent with the literature that considers financial behavior as a combination of psychological and contextual factors (Günther et al., 2025). Further studies could use better measures of financial literacy, expanded financial-literacy measures, and more objective measures of observed financial literacy effects before the analysis. More comprehensive and reliable multi-item scales of financial literacy, more expanded financial-literacy measures, and direct measures of perceived financial literacy and preregistered tests of practically meaningful effects could be used in future financial-literacy research. These enhancements would enable investigators to check if it is actual modest relationships or basic reporting errors which masked the real effect.

5. Conclusion

The present study investigated six of the behavioral biases and their relationships with retirement planning and risk tolerance and equity-oriented investment options in the context of higher-education employees in the National Capital Region of India (NCR) with a sample of n = 420. There were no significant (following multiple-testing correction) differences across any demographic on behavioral-bias scores. The financial literacy variables were virtually unrelated; between them, the range of their Pearson correlations was from around -0.08 up to 0.09. Only 0.4% of the variance of retirement planning was accounted for by the regression equation that contained the financial literacy variables ($R^2 = 0.004$). Financial literacy was not significantly related to financial retirement planning, and had no moderation effects on the relationships between behavioral biases and financial retirement planning. Likewise, none of the predictors of the focus was significantly related to equity orientation or risk tolerance. The model for girls in terms of retirement planning, however, showed a lower score for women than men, though, ($B = -0.131$, $SE = 0.041$, $p<.01$), and the finding should be treated with some caution, and confirmed via other studies.

The main contribution is the understanding from the readers of the importance of quality of measurement in the context of studying behavioral finance. Limited conclusions about underlying constructs are possible due to the very low internal consistency of the composite measures. Therefore, results do not rule out the presence of behavioral biases in financial decision making. On a practical level, institutions could test saving adequacy measures, offering services to qualified financial advisors and conducting financial education programs without relying on assumptions about demographics. The limitations of this study include lack of reliability with the scales, limited sampling, self-reported measures and the use of a cross-sectional design. Future research should confirm multi-item scales using confirmatory factor analysis, include further and more discriminating measures or tests of financial knowledge, and utilize a longitudinal or experimental design to establish causal relationships and test interventions among a variety of financial occupations.

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Data Availability

Data is available at reasonable request

Fundings

No Fundings

Conflict of Interest

No Conflict of Interest

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